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Boeri, M., & Longo, A. (2017). The importance of regret minimization in the choice for renewable energy programmes: evidence from a discrete choice experiment. *Energy Economics*, *63*, 253-260. https://doi.org/10.1016/j.eneco.2017.03.005

Published in:
Energy Economics

Document Version:
Peer reviewed version

The importance of regret minimization in the choice for renewable energy programmes: evidence from a discrete choice experiment

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Abstract

This study provides a methodologically rigorous attempt to disentangle the impact of various factors - unobserved heterogeneity, information and environmental attitudes - on the inclination of individuals to exhibit either a utility maximization or a regret minimization behaviour in a discrete choice experiment for renewable energy programmes described by four attributes: greenhouse gas emissions, power outages, employment in the energy sector, and electricity bill. We explore the ability of different models - multinomial logit, random parameters logit, and hybrid latent class – and of different choice paradigms - utility maximization and regret minimization - in explaining people's choices for renewable energy programmes. The "pure" random regret random parameters logit model explains the choices of our respondents better than other models, indicating that regret is an important choice paradigm, and that choices for renewable energy programmes are mostly driven by regret, rather than by rejoice. In particular, we find that our respondents' choices are driven more by changes in greenhouse gas emissions than by reductions in power outages. Finally, we find that changing the level of information to one attribute has no effect on choices, and that being member of an environmental organization makes a respondent more likely to be associated with the utility maximization choice framework.

***Keywords**:* Random Regret Minimization; Random Utility Maximization; renewable energy; greenhouse gas emissions; discrete choice experiments.

JEL: Q42, Q51

Highlights

- First paper to use the random regret minimization choice paradigm in energy economics

- With a hybrid latent class model, choices conform to either utility or pure random regret
- The pure random regret random parameters logit model outperforms other models
- Reducing greenhouse gas emissions is more important than reducing power outages

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1. Introduction and motivation

Stated discrete choice experiments (DCE) are widely employed to analyse citizens' preferences for environmental goods and services, such as the supply of renewable energy (see Goett et al. 2000; Roe et al. 2001; Bergmann et al. 2006, Scarpa and Willis 2010, Meyerhoff et al. 2010, Mariel et al. 2015). Traditionally, when analysing DCE data, researchers have relied on the Random Utility Maximization (RUM) model that assumes that respondents select the options that maximize their expected utility (McFadden, 1974, Train, 2009). However, several studies have suggested that respondents may be affected by bounded rationality when answering DCE questions (DeShazo and Fermo, 2004; Araña and León, 2009; Alemu et al, 2013). In particular, Chorus (2010, 2012a, 2012b) has indicated that a model that investigates regret minimization – the Random Regret Minimization (RRM) model – as a driver of choice, can be suitable for the analysis of DCE data (Chorus et al. 2014, van Cranenburgh et al, 2015). Differently from the RUM specification, the RRM is based on the assumption that, when choosing, individuals aim to minimize their anticipated regret, rather than to maximize their expected utility. In this context, regret is defined as what one experiences when a non-chosen alternative performs better than a chosen one, on one or more attributes.

Regret research originated in economics (Bell, 1982; Loomes and Sugden, 1982), and psychology (Gilovich and Medvec, 1995; Kahneman and Tversky, 1982; Zeelenberg and

Pieters, 2007). Regret has been found to be an important determinant of choice behaviour in different domains, including purchasing (Simonson, 1992; Hensher et al, 2013), transport (Chorus et al, 2008; Guevara et al, 2014; van Cranenburgh et al, 2015), recreation (Thiene et al, 2012; Boeri et al, 2012), and health (Boeri et al, 2013; de Bekker-Grob and Chorus, 2013). Previous studies have found that the two models – RUM and RRM – generate different elasticity values and different probabilities forecasting, implying different policy appraisals (Thiene et al. 2012, Boeri and Masiero 2014). This study provides a methodologically rigorous attempt to disentangle the impact of various factors - unobserved heterogeneity, information and environmental attitudes - on the inclination of individuals to exhibit either a utility maximization or a regret minimization behaviour in a DCE for renewable energy programmes described by four attributes: greenhouse gas emissions, power outages, employment in the energy sector, and electricity bill. In addition, we explore the concept of regret aversion to further understand respondents' behaviour (van Cranenburgh et al, 2015). To our knowledge, no study has used the RRM model to investigate the choices of renewable energy programmes.

Firstly, we investigate the performance of the two choice paradigms when answering the DCE questions by running multinomial logit models (MNLs) under the RUM framework and the RRM framework. We then explore unobserved heterogeneity by estimating Random Parameters Logit (RPL) models under both choice paradigms. Next, we employ a latent class (LC) model - a hybrid model incorporating both choice paradigms, as suggested by Hess et al. (2012), Boeri et al. (2014) and van Cranenburgh et al. (2015) - to investigate how respondents' characteristics, including environmental attitudes, impact on the adoption of the two different choice behaviours, RUM or RRM. Afterwards, we explore how varying the level of information on the power outages attribute affects respondents. Specifically, we split our respondents into two sub-samples and provide additional information on the power outages attribute to one sub-sample to explore whether this treatment produces an impact on the estimated preferences structure.

We find that bounded rationality plays an important role in the choices for renewable energy programmes, as the RRM explains respondents' behaviour well. Our results are robust: adding more information to the power outages attribute does not affect either the preference structure or the probability of adopting a particular choice paradigm. On a final note, we also find little evidence that personal characteristics, except membership to an environmental organization, make a respondent less likely to exhibit a rational decision making process.

The remaining of the paper is structured as follows. Section 2 describes the methodology; section 3 introduces the case study; section 4 presents the results; section 5 concludes the paper.

2. Method

2.1 Modelling DCE data: Utility and Regret

We assume that, whilst choosing among alternative hypothetical policies for renewable energy, respondents either maximize their utility or minimize their regret. The former idea is grounded on the utility maximization theory (Thurstone, 1927; Manski, 1977), which is well established and widely used in modelling DCE data. Considering the traditional respondents' utility function:

$$U_{nit} = \beta' X_{nit} + \varepsilon_{nit}, \qquad (1)$$

where X is a vector of attributes observed for respondent *n* while choosing alternative *i* in the choice occasion *t*, β is a vector of parameters to be estimated and ε is the unobserved part of the utility assumed to be identically and independently Gumbel-distributed (i.e. Extreme Value Type I). In this context, the probability of choosing alternative *i* over any other alternative *j* in the choice set *t* is represented by a multinomial logit model (RU-MNL) as described by McFadden (1974):

$$Pr_{nit}^{RU} = \frac{e^{\mu V_{nit}}}{\sum_{j=1}^{J} e^{\mu V_{njt}}}, \qquad (2)$$

Where $V_{nit} = \beta' X_{nit}$ and μ is the scale parameter of the Gumbel error.

The psychological notion that regret can be an important determinant of choice behaviour (Loomes and Sugden, 1982) originated what has become known as RRM approach (Chorus, 2010), which postulates that, when choosing alternative *i* among *j* alternatives in the choice task *t*, decision-makers aim to minimize anticipated regret. The regret function minimized by respondent *n* is:

$$\Psi_{nit} = \vartheta' R_{nit} + \omega_{nit}, \qquad (3)$$

where ϑ is a vector of parameters to be estimated and ω is the unobserved part of regret Gumbel-distributed (i.e. Extreme Value Type I). The observed part of the regret function,$R_{nit} = \sum_{j\neq i} \sum_{m=1..,M} \lambda_m \ln\left(1 + e^{\frac{\theta_m}{\lambda_m}(x_{jm} - x_{im})}\right)$ represents the sum of all so-called binary regrets associated with the bilateral comparison of alternative *i* with all the other alternatives *j* in the choice set. This comparison is done for all attributes *m*. The parameter θ_m captures the slope of the regret-function for attribute *m* and the parameter λ_m captures regret aversion for the attribute *m*. Recalling that minimizing the random regret is mathematically equivalent to maximizing the negative of the random regret, the probability for individual *n* of choosing alternative *i* over any other alternative *j* in the choice set *t* is given by the multinomial logit based on RRM (RR-MNL):

$$Pr_{nit}^{RR} = \frac{e^{\mu(-R_{nit})}}{\sum_{j=1}^{J} e^{\mu(-R_{njt})}}, \qquad (4)$$

The classical RRM model, originally proposed by Chorus (2010), assumes that the error-variances λ in the logsum transformation presented above are normalized to $\pi^2/6$. More recently, van Cranenburgh et al. (2015) relaxed this assumption and allowed the variance of implicit errors in the regret logsum to be estimated along with the preference weights θ_m to explore regret aversion. This model is the λRRM (λRR-MNL). In this context, λ determines the "smoothness", or linearity, of the regret function. A value of this parameter larger (smaller) than one implies that the degree of regret aversion is smaller (larger) than implicitly imposed by the classical RRM model. If the parameter is statistically indistinguishable from one, the classical RRM model is the best representation of the choice behaviours underlying the data, while if the parameter is large, the regret function is linear and the model generates the same choice probabilities as the RUM model. Finally, if the parameter is not different from zero, the regret function is similar to the original formulation: only regret matters and rejoice is irrelevant. The obtained model is the 'pure-RRM' (van Cranenburgh et al. 2015) [1].

[1] As the parameter λ could be confused with the scale parameter in the logit model (μ), it is important to highlight that the two parameters are originated from two different concepts. We note, on a side, that the scale parameter μ remains an additional parameter which is confounded and, therefore, fixed to one in most occasions, but that can be estimated under both choice paradigms. To avoid confusion between μ and λ we changed the name adopted by Van Cranenburgh et al. (2015) from μRRM to λRRM model.

2.2 Unobserved heterogeneity

The MNL models are quite restrictive, as they assume that all respondents have the same preferences. A more flexible model, the RPL, can be used to explore how respondents' heterogeneity affects choices. As highlighted by Chorus (2012), and described in Boeri and Masiero (2014), the extension of RRM models to RPL is straightforward. In the case of RUM, the RPL is derived by integrating the product of logit probabilities over the distribution of β:

$$Pr(y_n^t \mid \beta_n, X_n) = \int \prod_{t=1}^{T} \frac{e^{\mu V_{int}}}{\sum_{j=1}^{J} e^{\mu V_{jnt}}} f(\beta) d\beta. \quad (5)$$

In the case of RRM, the RPL is derived by integrating the product of logit probabilities over the distribution of θ:

$$Pr(y_n^t \mid \theta_n, X_n) = \int \prod_{t=1}^{T} \frac{e^{\mu(-R_{int})}}{\sum_{j=1}^{J} e^{\mu(-R_{jnt})}} f(\theta) d\theta. \quad (6)$$

We will estimate the RPL in equation 6 and explore regret aversion.

2.3 Hybrid choice behaviour model

Both the MNL and the RPL models treat all choices as either utility or regret. However, it is reasonable to assume that some choices may be explained better by the RUM and some others by the RRM. As suggested by Hess et al. (2012) and Boeri et al (2014), it is possible to accommodate for such a behaviour using a two-class latent class (LC) model (also referred to as probabilistic decision processes) where class 1 consists of RUM decision makers and class 2 of RRM decision makers. Under this setting, the probability of a sequence of choices is:

$$\Pr(y_{Tn}|X_{nit}) = \prod_{t=1}^{T} \left(\pi_V \, Pr_{nit}^{RU} + (1 - \pi_V) \, Pr_{nit}^{RR} \right). \quad (7)$$

Note that the choice probability in each class can be described by a MNL model (equations 2 and 4) or a RPL model to account for heterogeneity (equations 5 and 6).

A second approach, which we follow in this study, was suggested by van Cranenburgh et al. (2015), and is based on the λRRM formulation that includes regret aversion. By estimating a LC model with three classes in which regret aversion is estimated, it is possible to investigate whether the data conform to the pure RRM (λ → 0), the classical RRM (λ → 1) or the RUM (λ → ∞) model, according to the estimated value of λ.

To explore how personal characteristics are more likely to be associated with a rational – utility maximization – or a bounded rational – regret minimization – choice model, we estimate a membership probability π_V for the class associated to the maximization of utility defined according to a logit process. We have:

$$ð_V = \frac{\exp(\alpha_c+\gamma_c' z_n)}{\exp(\alpha_c+\gamma_c' z_n)+1} \ , \qquad (8)$$

where z_n is a vector of socio-economic covariates characterizing respondent n, and γ_c is the vector of associated parameters subject to estimation, while α_c is a class-specific constant.

The analyses were performed with Biogeme 2.4 (see Bierlaire, 2003, 2009), a flexible version of Biogeme based on Python. The models were estimated using the CFSQP algorithm (Lawrence et al., 1997) and the RPL formulations were estimated through maximum simulated likelihood (MSL) with 500 quasi-random draws via Latin-hypercube sampling (see Hess et al., 2006, for further details).

2.4 Information effect

Next, to investigate the suitability of the rational-based RUM and the bounded rational RRM model in analysing the data for the choice of renewable energy programmes, we explore the effect of changing the level of information provided to respondents for one of the attributes of the DCE. Several studies have investigated the effect of information on stated preferences studies (Boyle, 1989; Rolfe et al, 2002; Bergstrom et al, 1990; Spash and Hanley, 1995; Gao and Schroeder, 2009; Alberini and Longo, 2009), but none has investigated the effect of information on the choice paradigm.

Additional information may act in two ways: it may influence whether a respondent chooses maximizing their utility or minimizing their regret and, within each choice paradigm, it may impact on the preferences' intensity and variance, as measured respectively by the estimated coefficients and scale parameter of the logit formulation. We have little a priori expectations on the effect of information on the choice paradigm. Additional information might reduce the complexity of the choice task, and make respondents more familiar with the goods they are evaluating (Aidt, 2000; Boeri et al, 2014). Under this hypothesis, one might expect respondents to rely more heavily on the utility maximization framework.

To test for the effect of information, we split our sample into two sub-samples, and provide additional information on the power outages attribute to one sub-sample.

The effect of information on the choice paradigm can be tested through a split sample analysis in three ways: by looking at the membership probability of the hybrid LC model, at the degree regret aversion, and at the preferences and variance of the logit models. In the hybrid model, the information effect can be assessed by adding, in the membership probability model, a dummy variable equal to one if a respondent receives additional information, and zero otherwise. Regret aversion can be investigated in each of the two sub-samples by estimating different λRRM models for different levels of λ.

To test for the impact on preferences or variance of different levels of information, both RU-MNL and RR-MNL models can be estimated on the two sub-samples, and both can include scale parameters (μ). It is therefore possible to test, under either choice paradigms assumptions, whether increasing the level of information on one attribute of the DCE has any impact on preferences or scale parameter, and therefore preferences variance, by comparing the log-likelihood (LL) functions, and hence the Akaike information criterion (AIC), of the MNL models estimated for the two sub-samples. Following Swait and Louviere (1993), we do this in two steps. Firstly, we test a null hypothesis of equality of the preference coefficient estimates against an alternative hypothesis that the coefficient estimates are different. Secondly, if this null hypothesis cannot be rejected, we examine differences in scales across subsamples (for more details on how the test is carried out, see Swait and Louviere, 1993).

3. The case study

We use the data from a DCE aimed at eliciting public preferences for hypothetical policies for the promotion of renewable energy described by four attributes: (i) annual percentage reduction in greenhouse gas emissions, (ii) duration of energy disruptions (black-outs), (iii) variation in the number of people employed in the energy sector and (iv) electricity bill increase. These attributes were chosen on the basis that energy policies in the UK aim to reduce greenhouse gas emissions, increase energy security, maintain employment or create new jobs at affordable prices for society (DTI, 2003, DECC, 2011). The selection of the attributes and their levels was finalized during the conduction of focus groups.

The first attribute, greenhouse gas emissions, indicates the percentage reduction of emission per year. Its levels, reductions by 1%, 2% and 3%, are based on the targets described by the UK Energy White Paper (DTI, 2003). The second attribute, black-outs, in the form of sudden unannounced energy shortages, takes the levels of 30, 60, 120 minutes of black-out per year, being the business as usual scenario 90 minutes per year. The third attribute describes the effects of the policy on employment. The increasing demand for renewable energy might, on the one hand, increase the number of jobs in the renewable energy sector, and, on the other hand, decrease the number of jobs in the fossil fuel energy sector. Moreover, being the private cost of renewable energy more expensive than fossil fuel energy, an increase in renewable energy might have macroeconomic consequences in the energy industry resulting in a total loss of jobs.[2] Focus groups discussions suggested to set the following levels for the attribute employment: 1000 new jobs, 1000 jobs lost, and no change in jobs in the UK energy sector. The values were calculated by assuming a hypothetical variation of about 0.5% in the total number of employees in the energy sector.[3] The final attribute is cost to the household, expressed as increases in the quarterly electricity bill. Its levels are an increase by £6, £16, £25 and £38 and they correspond to an increase by 10%, 25%, 40%, and 60% from the average electricity bill in the UK.[4] Table 1 summarises the attributes and their levels for the present study.

[Table 1 should be approximately here]

When describing the black-out attribute, respondents in sub-sample 2 were given the following description:

"As the demand for electricity increases, it is likely that we will experience an increase in the number and in the length of black-outs since the grid might not be able to satisfy the total

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[2] Firms might face higher prices. This could lead to an increase in wages in such a way that the unemployment rate would need to increase to balance the effect. On the other way, as pointed out by an anonymous reviewer, shifting to renewable energy – being more labour intensive than fossil fuel energy – might have a positive effect on jobs.

[3] According to the Office for National Statistics (2005), the total number of employees in the Energy and Water Industry Sector in the UK during the second quarter of 2005 was 177,000.

[4] The average annual electricity bill in the UK according to the National Statistics is equal to £251 (DTI, 2005a; Table 2.2.2). The electricity consumption in 2003 was equal to 337.443 billion kWh (IEA, 2003).

demand. *Having black-outs means that there is no electricity. As a consequence, we would have no light at home, the fridge would not work, so wouldn't the lifts, etc. Also the industrial production would suffer.* Using renewable sources, we increase the number of the sources from which we can produce electricity, which lowers the risk associated with the dependence of foreign energy suppliers so that the disruption of one of the sources will have smaller effects on the total energy supply."

Sub-sample 1 was not given the information in italics as reported in the above text. Sub-sample 2, therefore, received some additional information on the effects of black-outs compared to sub-sample 1.

In each choice task respondents were asked to indicate their preferred policy out of a choice set with three alternatives: two experimentally designed alternatives and the current situation. To create the pairs of alternative hypothetical policies, we opted for a fractional factorial design (Louviere et al, 2000), using the %MktEx SAS macro for an efficient experimental design (Kuhfeld, 2010). We then selected two of these alternatives, but discarded pairs containing dominated or identical alternatives and prepared six different versions of the questionnaire with six choice tasks each.[5] An example of choice experiment is shown in Figure 1.

[Figure 1 should be approximately here]

The survey was administered in person to 300 respondents intercepted in shopping areas, public parks and other central areas of Bath, England, in July and August 2005 by professional interviewers who were instructed to interview an even number of men and

[5] More efficient designing methods for DCE have been developed since the seminal work by Ferrini and Scarpa (2007), however when the survey instrument was developed, it was common practice to use fractional factorial designs, as proposed by Louviere et al. (2000).

women and to ensure the desired proportions of respondents in various age groups. To mitigate possible biases in the sample, interviewers were instructed to follow the common practice of stopping potential respondents every 7th person passing by. We chose to interview people through in-person interviews to guarantee a high quality in the answers. The budget constraint of this study limited our analysis to sample residents of Bath and North East Somerset. The results presented in this study should therefore be interpreted with caution: they are not representative of the UK population, but of the residents of a quite wealthy medium sized town of the South of the UK.[6]

4. Results

4.1 Descriptive statistics

Our average respondent is 35 years old, has an annual gross household income of about £37,000, and pays £70 per quarter on electricity bill. About 34% does not report how much they pay for electricity, almost 31% have electric heating, and 22% are members of an environmental organization. After the DCE questions, we investigated altruistic behaviour by asking respondents whether their choices were driven by what they considered be best for society or for their household. We find that 75.67% choose the options that they considered best for society, with the remaining 24.33% choosing what is better for their household. Of the 300 respondents, 132 (44%) received the version with additional information on black-outs (subsample 2), and the remaining 168 (56%) received the baseline questionnaire (subsample 1). Table 2 reports the descriptive statistics of the variables used in the econometric models.

[6] For a complete description of the survey see Longo et al. (2008).

[Table 2 should be approximately here]

4.2 Preferences and choice behaviour analysis

Table 3 reports the output of the three MNL models specifications: the RU-MNL, the RR-MNL, and the λRR-MNL. By examining the log-likelihood value of the models, we notice that the λRR-MNL model fits the data better than both the RU-MNL and the RR-MNL. This result appears to support our assumption that regret minimization explains the choices for hypothetical programmes for promoting renewable energy better than utility maximization does. Furthermore, as the λRR-MNL with a parameter for regret aversion smaller than one fits the data better than the other models, it is possible to argue that the degree of regret aversion is larger than implicitly imposed by the classical RRM model.

Both findings support the theoretical prediction that anticipated regret seems to drive choices perceived as important and difficult, when the decision-maker expects to receive feedback about chosen and non-chosen options in the short term, and when the decision-maker believes that he or she will be held accountable for the choices made (Zeelenberg, M., 1999). In our case, respondents make choices on behalf of their household, therefore, it is possible that regret minimizations plays an important role in explaining their choices because respondents' decisions may affect households' wellbeing.

[Table 3 about here.]

The output shows that for both models all parameters are highly statistically significant and have the expected signs. However, the interpretation of the coefficients from the models under the two choice paradigms is not directly comparable. In fact, a positive and significant coefficient in the RR-MNL and λRR-MNL, such as the one for the reduction of greenhouse gas emissions and the number of jobs, suggests that regret increases as the level of those attributes in a non-chosen hypothetical policy increases, compared to the level of the attributes characterizing the chosen alternative. Similarly, the negative coefficients for price, or for the minutes of unexpected black-outs, suggest that regret decreases as the difference in levels for price, or for minutes of black-outs, between the chosen and the non-chosen alternative increases. When these differences increase, non-chosen alternatives become less attractive as they are more expensive or entail longer periods of energy disruptions.

4.3 Unobserved heterogeneity results: RPL models

We relax the assumption of homogeneity of preferences by estimating RPL models under both choice paradigms. We estimate four models: RU-RPL, the classical RR-RPL, the λRR-RPL model that explores regret aversion, and the pure RR-RPL model. The results, reported in Table 4, show that, also in this case, regret minimization fits the data better than the utility maximization model. The λRR-RPL shows that, when we explore the effect of regret aversion, λ is not statistically significant from zero. This means that the λRR-RPL collapses to the pure RR-RPL model.[7] The RPL models results show that the mean of the normal distributions are slightly higher in absolute terms compared to the results from the MNL models. These means are accompanied by statistically significant standard deviations, indicating that respondents have heterogeneous preferences for the different attributes.

[7] The pure RRM model parameters coefficients have to be constrained to be either positive or negative (van Cranenburgh et al. 2015). Therefore, we estimated our pure RRM model assuming constrained normal distributions, whilst the RU-RPL and λRR-RPL models were estimated assuming normal distributions. This did not have a major impact on the model fit and, as predicted, the pure RR-RPL model reaches a good approximation of the λRR-RPL model.

[Table 4 about here.]

4.4 Observed heterogeneity results: hybrid model

To further explore preferences heterogeneity, we run a three-class LC model where each class is composed by a λRRM with the coefficient for regret aversion free to vary in each class to test whether the three classes approximate to RU-MNL ($\lambda \rightarrow \infty$), pure RRM ($\lambda \rightarrow 0$), or classical RRM ($\lambda \rightarrow 1$) (van Cranenburgh et al., 2015). The results of this model highlight the presence of one class with λ equal to 0 (pure RR-MNL), a second class with very high λ (RU-MNL) and a third class with regret aversion not significantly different from zero (pure RR-MNL) and with very low and not statistically significant membership probability. Given numerical problems for the estimations when λ is very high or close to zero, the model was not identifiable. Therefore, we replaced the classes where λ was equal to zero and where it was very high with a pure RR-MNL and with a RU-MNL respectively. We decided to eliminate the third class from the final model specification because the additional parameters were not justified by the increased LL of the model and one of the two pure RR-MNL classes was associated with a very low and not statistically significant membership probability. The output of this model, in which a class membership probability to explore observed heterogeneity is estimated following a logit model, is presented in Table 5.

[Table 5 about here.]

The coefficients estimates are consistent with the findings of our previous modelling approaches: respondents prefer reductions in greenhouse gas emissions and increase in jobs, dislike black-outs and higher costs for the implementation of the hypothetical programmes. The class membership probability model shows that respondents' choices are described better by a pure RR-MNL, as the regret model explains about 55% of the choices. The coefficient for the additional information on black-outs associated with the RU-MNL class is estimated with a positive but not statistically significant sign, indicating that increasing the amount of information has no statistically significant effect on the probability of respondents adopting a utility maximization or a regret minimization choice paradigm. When we look at what determine the membership probability, we find that being member of an environmental organization is the only element that significantly increases the probability that a respondent employs the utility maximization framework when choosing. These results provide evidence that, whilst a small change in the level of information has negligible effects on the choice paradigm, having a strong preference towards the environment makes a respondent more likely to choose the utility maximization framework. When we further attempted to account for preferences heterogeneity within the hybrid models, we found not identifiable models, with model fits worse than the RPL models, suggesting that when considering preference heterogeneity the best model is the pure RR-RPL model (Table 4).

4.5 Information effects: further results

To explore whether small changes in the description of one attribute impact on the structure of preferences or variance (scale), we performed the test proposed by Swait and Louviere (1993) under both RUM and RRM specifications. For each specification, we estimated four models: (a) only sub-sample 1, respondents with no additional information on black-outs; (b) only sub-sample 2, respondents with additional information on black-outs; (c) pooled dataset with both sub-samples, not controlling for differences in scale between the two sub-samples; (d) pooled dataset with both sub-samples, controlling for differences in scale between the two sub-samples.

Models (a), (b) and (c) are used to test the null hypothesis of no differences in preferences between sub-samples 1 and 2, while Models (c) and (d) are used to test the null hypothesis of no differences in scale parameters between the two sub-samples. The latter can be tested only if we reject the former hypothesis; in fact, if preferences are different across sub-samples, differences in the scale parameter of the logit across sub-samples cannot be disentangled from preferences.

[Table 6 about here.]

In both tests, under both choice paradigms, the values estimated are smaller than the critical values of the χ^2 distribution, as shown by the results of the test proposed by Swait and Louviere (1993) for the MNL models reported in Table 6. Similar results were found with the RPL models. Therefore, since we cannot reject the null hypotheses of preferences or scale homogeneity between sub-samples 1 and 2, we conclude that the additional information on the attribute black-out has no impact on either preferences or the scale factor in our data.

When we further explore the impact of information on regret aversion for each subsample by estimating different λRRM models, we do not find differences across subsamples and conclude, once more, that the additional information has no effect.

4.6 Choice probability forecasting

We can use the results from the RU-RPL and the pure RR-RPL models of table 4 to compare the choice probability forecasting of the two models for hypothetical renewable energy programmes to appreciate the insights from the use of the RRM model for policy, as shown in table 7.

[Table 7 about here.]

Consider a policy scenario 1, with two programmes, A and B, and the current situation. Programme A is described by 30 minutes of black-out per year, 1% annual reduction in greenhouse gas emissions, no change in employment, and an increase in the electricity bill of £25 per quarter. Programme B is characterized by 60 minutes of black-out per year, 2% annual reduction in greenhouse gas emissions, no change in employment and an increased cost to the respondent of £16 per quarter. The current situation entails no change in the current levels of 90 minutes of black-out per year, no reduction in greenhouse gas emissions, no change in employment and no increase in the electricity bill. Given these three options, the RU-RPL model forecast indicates that the likelihood of choosing the three alternatives are: 23.9% for programme A, 72.1% for programme B and 4% for the current situation. The choice forecasts emerging from using the pure RR-RPL are: 18.9% for programme A, 76.7% for programme B and 4.4% for the current situation. Both models indicate a strong preference for programme B.

However, in a policy scenario 2, if programme C were offered instead of B, identical to B in everything except for the black-out level which, rather than having 60 minutes of black-out per year, offered 120 minutes of black out per year, the RUM choice probabilities forecast would be quite different to the RRM ones. Under this new scenario, the pure RR-RPL model choice forecasts are 31.3% for programme A, 61.4% for programme C and 7.3% for the current situation, whilst for the RU-RPL model, the likelihood of choosing the three alternatives are now: 43.4% for programme A, 49.5% for programme C and 7.1% for the current situation. This result shows that, with the pure RR-RPL model, programme C is much more likely to be chosen than model A, as the majority of respondents would prefer C, whilst with the RU-RPL model, the appeal of programme C is less clear compared to programme A.

These results are important for policy purposes. They show that the RRM model provides clearer indication that programme C is preferred than the other two alternatives in policy scenario 2. A policy maker should be confident in implementing programme C from a bundle including A, C and the current situation. If the policy maker employed only the RUM model, the decision whether to implement A or C would be less clear. These results also show that the RRM model indicates that our respondents have a stronger preference for a reduction in greenhouse gas emissions, compared to improvements in power outages, than the RUM model would suggest.

5. Conclusions

This study explored the behavioural insights from the regret minimization and the utility maximization frameworks in the choices for hypothetical programmes to promote renewable energy described by four attributes: greenhouse gas emissions, power outages, employment in the energy sector, and electricity bill. We investigated differences in choice behaviour for different characteristics of the respondents, different levels of information, and for different specifications of the models. We explored the performance of utility maximization and regret minimization models using MNL, RPL, and LC models. We found little evidence of observed heterogeneity: only respondents who are members of environmental organizations are more likely to belong to a class where choices are explained better by the utility maximization framework. Adding some information to the power outages attribute of the DCE does not affect choices.

The regret minimization framework fits our data better than the utility maximization model. Given the importance of regret in the choice for renewable energy programmes, a policy aimed at developing renewable energy should take into consideration that the effects of the interventions may be different according to the choice paradigm used by decision makers in analysing the preferences of the respondents.

As our sample is representative of a wealthy, small city in the south of England, and comprises respondents intercepted on the street (we could only interview people who went out during the time of the survey, and those who went out more often were more likely to be interviewed), we warn the reader to use some caution when making policy recommendations based on our results. However, we do emphasize that if a policy maker does not consider the importance of the choice paradigm, choice forecasting may be inaccurate.

When we explored the importance of regret aversion, we noticed that the pure RR-RPL model explains the choices of our respondents better than other models. In this model, there are very strong differences between the regret generated by a loss and the rejoice generated by an equivalent gain: rejoice has a very low importance – close to zero – and respondents primarily aim at minimizing regret. This suggests that when analysing renewable energy programmes, our respondents' bounded rationality leads them to choose options that minimize their possible losses. Possible gains are not so important, as they contribute very little to the regret minimization function.

This result bears some similarities with prospect theory, which states that people make decisions based on the potential value of losses and gains rather than the final outcome, and that people value losses more heavily than gains (Kahneman and Tversky, 1979). Following Harinck et al. (2007), as loss aversion is particularly important for large outcomes, finding evidence that our respondents consider highly important the regret associated with their choices, whilst the rejoice associated with their choices is negligible, we would conclude that our respondents consider large the outcome associated with renewable energy programmes, and especially with the greenhouse gas emissions reduction attribute.

Future research should investigate for small outcomes whether pure regret minimization, regret minimization that gives a strong weight to rejoice ($\lambda > 1$), or utility maximization explains choices better. If Harinck et al. (2007)'s intuition that small losses are more heavily discounted than large ones translates into discrete choice behaviour, it is reasonable to assume that for small outcomes one can expect either the utility maximization or the λRRM to explain choices better than the pure RRM model.

This research could also be expanded by looking at whether varying the level of information on more than one attribute maintains the preferences of the respondents stable across the choice paradigms and increases the probability of respondents using the RUM choice paradigm. Finally, in this paper we assumed that regret aversion is homogenous across attributes and respondents, an assumption that may be relaxed in the future, as suggested in van Cranenburgh et al. (2015).

Acknowledgements

The authors wish to thank the participants to the "Discrete Choice Modelling Workshop – Warsaw 2016", the UKCRC Centre of Excellence for Public Health Northern Ireland MRC Grant No. MR/K023241/1; the Financial Aid Programme for Researchers 2014 of BIZKAIA: TALENT "Transportation Policies: Emissions Reductions, Public Health Benefits, and Acceptability"; and the Spanish Ministry of Economy and Competitiveness through Grant No. ECO2014-52587-R.

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Choice set 1:

Characteristics	Policy A	Policy B	Neither
Greenhouse Gasses emissions	2% reduction	3% reduction	no greenhouse gasses emissions reduction
Black-outs	120 min/per year	30 min/per year	no new actions to prevent future black-outs
Employment	0 new jobs	-1,000 jobs	no employment change in the sector
Price	£6.5 per quarter	£16 per quarter	no price increase in the electric bills
Which policy would you choose?	☐	☐	☐

Figure 1. A choice experiment question used in the questionnaire.

Table 1. Attributes and their levels for the choice experiments

Attribute	Level 1	Level 2	Level 3	Level 4	Status quo
Annual reduction in greenhouse gases emissions due to renewable energy increase (3 levels)	1%	2%	3%	-	no additional greenhouse gases emissions reduction
Annual length of electricity shortages in minutes (3 levels)	30	60	120	-	90
Change in number of employees in the electricity sector (3 levels)	+1000	-1000	0	-	no employment change in the energy sector
Increase in electricity bill in £ (4 levels)	6	16	25	38	no price increase in the electricity bill

Table 2. Descriptive statistics

Variable (acronym used in regressions)	Observations	Sample average or percent (Standard deviation)
Age	300	35.75 (12.52)
Electricity bill in £ (BILL)	197	70.86 (38.78)
Categorical variables (dummy coded)		
Married (MARRIED)	300	28.67%
Member of environmental organizations (ENV_ORG)	300	22.00%
Did not state the electricity bill (NOBILL)	300	34.33%
Answered DCE questions as best for society (SOCIETY_ CHOICE)	300	75.67%
Answered DCE questions as best for the individual	300	24.33%
Received the additional information on black-outs (BLACKOUT_INFO)	300	44.00%
BLACKOUT_INFO	300	44.00%

Table 3: Estimations results for RU-MNL and RR-MNL models (1,800 observations)

	RU-MNL		RR-MNL		λRR-MNL	
Attribute	**Coeff.**	**|t-stat|**	**Coeff.**	**|t-stat|**	**Coeff.**	**|t-stat|**
BLACK-OUT	-0.001	9.17	-0.007	9.71	-0.006	8.40
GREENHOUSE GASES REDUCTION	0.928	13.00	0.751	14.76	0.727	14.48
JOBS	0.0007	9.79	0.0005	11.61	0.0004	9.28
PRICE	-0.013	2.42	-0.015	4.36	-0.012	3.60
λ					0.393	2.39
Log-likelihood (LL)	-1535.497		-1512.959		-1508.409	
Parameters	4		4		5	

Table 4: Estimations results RU-RPL and RR-RPL (1,800 observations – 250 MLHS draws)

	RU-RPL		RR-RPL		λRR-RPL		pure RR-RPL	
Attribute	**Coeff.**	**|t-stat|**	**Coeff.**	**|t-stat|**	**Coeff.**	**|t-stat|**	**Coeff.**	**|t-stat|**
BLACK-OUT	-0.0162	9.70	-0.0118	10.29	-0.0123	10.12	-0.0121	9.91
GREENHOUSE GASES REDUCTION	1.39	11.69	1.45	11.52	1.53	12.03	1.49	11.74
JOBS	0.0011	8.94	0.0008	10.49	0.0008	10.29	0.0008	10.42
PRICE	-0.0221	3.27	-0.0320	7.02	-0.0313	7.62	-0.0304	7.32
λ					0.12	1.15		
Standard deviations								
BLACK-OUT	0.0124	5.87	0.0078	4.70	0.00854	5.41	0.00984	5.85
GREENHOUSE GASES REDUCTION	0.759	9.12	0.748	9.11	-0.825	9.1	-0.896	10.13
JOBS	0.0012	10.27	0.0007	10.04	0.00065	9.67	0.00073	10.16
Log-likelihood (LL)	-1413.100		-1381.615		-1367.912		-1370.022	
Parameters	7		7		8		7	

Table 5: Latent Class model estimates with one class for RU-MNL and one for PRR-MNL and socio-economic and attitudinal variables to explain membership probability (1,800 observations – 250 MLHS draws)

	RU-MNL-class		pure RR-MNL-class	
Attribute	**Coeff.**	**|t-stat|**	**Coeff.**	**|t-stat|**
BLACK-OUT	-0.017	6.90	-0.0077	7.35
GREENHOUSE GASES REDUCTION	1.81	7.72	0.713	12.52
JOBS	0.00032	1.78	0.00086	11.59
PRICE	-0.0196	1.61	-0.0275	6.97
Membership probability model	45.59%		54.41%	
INTERCEPT	-2.75	1.78		
BLACKOUT_INFO	0.261	0.91		
SOCIETY_CHOICE	0.0331	0.1		
BILL[a]	-0.0035	0.75		
NOBILL	-0.312	0.69		
AGE	0.11	1.53		
AGE_SQUARED	-0.001	1.14		
MARRIED	-0.211	0.62		
ENV_ORG	0.846	2.49		
Log-likelihood (LL)	-1,394.238			
Number of parameters	17			

[a] To avoid losing observations, we set the value of BILL equal to zero when there was a missing observation for that variable. By introducing the dummy variable NOBILL equal to one when there was a missing observation for BILL and zero otherwise in the model allows us to capture any statistical difference between respondents that reported and those that did not report their energy bill (see Alberini and Longo, 2009).

Table 6: testing differences in preferences and scale for additional information under RU-MNL and RR-MNL

	RU-MNL		RR-MNL	
specification	**LL**	**K**	**LL**	**K**
pooled model (info and not) no scale	-1535.497	4	-1512.959	4
scaled model	-1534.634	5	-1511.926	5
only not added info	-871.174	4	-856.985	4
only additional info	-661.825	4	-654.891	4

TEST under RU-MNL model	**TEST**	**χ at P = 0.10**	**P = 0.05**	**P = 0.01**
H1a (dgf = 9)	3.27	14.68	16.92	21.67
H1b (dgf = 1)	1.73	2.71	3.84	6.63
TEST under RR-MNL model	**TEST**	**χ at P = 0.10**	**P = 0.05**	**P = 0.01**
H1a (dgf = 9)	0.10	14.68	16.92	21.67
H1b (dgf = 1)	2.07	2.71	3.84	6.63

*dgf = Degrees of Freedom

Table 7: Choice probability forecasts

Policy scenario 1	A		B		Current situation	
	Probability (%)	Confidence interval	Probability (%)	Confidence interval	Probability (%)	Confidence interval
RU-RPL	23.94	[18.95-28.93]	72.10	[67.30-76.90]	3.92	[3.73-4.11]
pure RR-RPL	18.90	[14.25-23.55]	76.70	[72.08-81.32]	4.41	[4.38-4.44]
Policy scenario 2	**A**		**C**		**Current situation**	
	Probability (%)	Confidence interval	Probability (%)	Confidence interval	Probability (%)	Confidence interval
RU-RPL	43.41	[42.04-44.79]	49.48	[48.44-50.53]	7.11	[6.78-7.44]
pure RR-RPL	31.29	[30.08-32.49]	61.42	[60.61-62.23]	7.29	[6.90-7.69]

A entails 30 minutes of black-out per year, 1% annual reduction in greenhouse gas emissions, no change in employment, and an increase in the electricity bill of £25 per quarter. B presents 60 minutes of black-out per year, 2% annual reduction in greenhouse gas emissions, no change in employment and an increased cost to the respondent of £16 per quarter. C offers 120 minutes of black-out per year, 2% annual reduction in greenhouse gas emissions, no change in employment and an increased cost to the respondent of £16 per quarter. The current situation entails no change in the current levels of 90 minutes of black-out per year, no reduction in greenhouse gas emissions, no change in employment and no increase in the electricity bill.